Self-organized Resource Allocation Based on Traffic Prediction for Load Imbalance in HetNets with NOMA

Jichen Jiang, Xi Li(✉), Hong Ji, and Heli Zhang

Key Laboratory of Universal Wireless Communications, Ministry of Education,
Beijing University of Posts and Telecommunications,
Beijing, People's Republic of China
{jiangjichen,lixi,jihong,zhangheli}@bupt.edu.cn

Abstract. With the development of mobile communication technology, the data traffic of wireless cellular network has grown rapidly in the past decade. Because of the various bandwidth-eager applications and users movement, load imbalance has become an increasing severe problem, impacting the user experience and communication efficiency. Especially, it may lead to the degrading of resource utilization and network performance. In this paper, we investigate this problem and propose a self-organized resource allocation algorithm that allocates the resource to somewhere that the resource is needed to deal with the load imbalance problem. The typical heterogeneous network with non-orthogonal multiple access (NOMA) is discussed. A traffic prediction model is applied to the NOMA system. Then the self-organized resource allocation is formulated as a mixed integer non-linear programming (MINP) problem aiming at maximizing the overall throughput. The optimization problem is hard to tackle so we propose an algorithm to obtain a suboptimal solution via quantum-behaved particle swarm optimization (QPSO) algorithm. To evaluate how the resource is allocated according to the data traffic requirements, an indicator called evolved balance factor (EBF) is proposed to jointly consider the resource utility and the distribution of data traffic. Simulation results show that the proposed algorithm achieves a better performance in the overall throughput compared with exiting schemes.

Keywords: Self-organized · Resource allocation · Traffic prediction
NOMA · Load imbalance

1 Introduction

As the mobile devices drastically increased over the past several years, the mobile data volume is experiencing an exponential growth. This growth not only increases the load pressure of the network, but also impacts resource utility. In order to face the challenge of providing higher data rate speed and system capacity, heterogeneous network with small cells and non-orthogonal multiple access

© ICST Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2018
L. Wang et al. (Eds.): QShine 2017, LNICST 234, pp. 55–65, 2018.
https://doi.org/10.1007/978-3-319-78078-8_6

(NOMA) technology are considered as the promising solutions to meet the users requirements and spectral efficiency [1–4]. In the NOMA-based heterogeneous networks (HetNets), due to the various bandwidth-eager applications and users movement, load imbalance is an important problem and may degrade the network performance obviously. Especially, the resource utility may be impacted. On one hand, the overall resource is short of use due to the rapidly increased throughput requirement; on the other hand, the traditional fixed resource allocation methods may result in low utility in local area. Therefore, how to allocate the resource properly according to the load imbalance condition is an interesting and necessary problem to investigate.

Resource allocation in NOMA and HetNets have many existing research results. Reference [1] proposes an optimal power allocation algorithm and an efficient user selection scheme for downlink NOMA system. The problem is formulated as an optimization problem that maximizes the weighted sum rate subjected to a power constraint and the algorithm is proved to be highly efficient through numeral results. Reference [5] provides an user paring and power allocation scheme in the 2-user NOMA system based on proportional fairness in which the proportional fairness is adopted as a key point to make tradeoff between transmission efficiency and user fairness. Reference [6] gives a complexity analysis on NOMA resource allocation and then provide an effective algorithm for multi-user power and channel allocation in NOMA system and propose a sub-optimal solution combining Lagrangian duality and dynamic programming.

Load imbalance has attracted the researchers' attention with existing work, such as the handover to neighbor cells, traffic scheduling and base station turning on/off [7–9]. Traffic prediction is another effective method, based on which further steps could be carried out to deal with the possible load imbalance condition. Reference [10] proposes a resource allocation scheme that pre-download the files requested by users according to the user trajectory prediction procedure to minimize the maximal transmission completion time. Reference [11] proposes a predictive energy-aware network selection and resource allocation algorithm in which a tradeoff between power consumption and traffic delay is achieved. Reference [12] provides an AP access scheme for multiple APs in user-centric ultra dense networks in which the access rules highlight the QoS of users and the system EE and a grouping evaluation model is set up based on several network performance indicators.

As to the load imbalance in NOMA-based HetNets with small base stations (SBSs), it is just the beginning in the relative research fields. In this paper, we solve the problem by traffic prediction and then scheduling the resource accordingly. A self-organized resource allocation algorithm based on traffic prediction (SORA-TP) is proposed to allocate the resource to somewhere that the resource is needed to deal with the load imbalance problem. The traffic demand is predicted by minimum mean square error (MMSE) model which is suitable for online traffic prediction due to its simple and fast feature. Then SBSs can use the results of prediction to allocate the resource automatically aiming at maximizing the overall throughput. In order to evaluate the performance of the algorithm, an indicator called evolved balance factor (EBF) is derived which indicates how the resource is allocated with the predicted data traffic. Then we formulate this problem as a mixed integer non-linear programming (MINP) problem and solve it by quantum-behaved particle swarm optimization (QPSO) [13] algorithm. Simulation results reveal that the performance of the proposed algorithm outperforms the existing algorithms.

The rest of this paper is organized as follows. In Sect. 2, the system model and the studied scenario are introduced. Section 3 presents the problem formulation and describes the proposed self-organized resource allocation algorithm, followed by simulation results in Sect. 4. Section 5 concludes our work.

2 System Model

2.1 NOMA-Based HetNet

We consider a downlink two-tier HetNet with NOMA where several users are randomly distributed in each cell, as shown in Fig. 1. The user set is denoted as $\mathcal{K}$, $\mathcal{K} = \{1, 2, \cdots, K\}$. Total bandwidth is W and is divided into N resource blocks (RB). The RB set is defined as $\mathcal{N} = \{1, 2, \cdots, N\}$, each with bandwidth B, $B = W/N$. The set of SBSs is defined as $\mathcal{J}$, $\mathcal{J} = \{1, 2, \cdots, J\}$. Factor g_{kj}^n is used to describe the channel gain between user k and SBS j on RB n. We assume that the SBS allocates the power to all RBs equally but each users are assigned with different power which is denoted as p_{kj}^n. Single antenna is used for both transmission and reception. Thus the received signal for user k with SBS j in n-th RB is given as

$$y_{kj}^n = \sqrt{p_{kj}^n} g_{kj}^n \xi_{kj}^n + \sum_{i=n+1}^{N} \xi_{ij}^n \sqrt{p_{ij}^n} g_{kj}^n + w_{kj}^n \tag{1}$$

where w_{kj}^n is the noise, ξ_{kj}^n is an indicator that describes the relationship between user k with SBS j RB n which is defined as

$$\xi_{kj}^n = \begin{cases} 1 & \text{user } k \text{ is served by SBS } j \text{ in RB } n \\ 0 & \text{otherwise} \end{cases}$$

In downlink NOMA, successive interference cancellation (SIC) is applied in user receivers. Users with better channel quality employ SIC to remove the inference from other users that have lower CQIs. For example, in Fig. 1, user 1 has better channel quality and the channel quality of user 2 is lower. So SIC receiver has to be used on user 2 to remove the interference from the transmission to user 2 while user 1 can decode the signal directly without SIC. We assume that users are defined in the descending order of signal-to-interference-plus-noise ratio (SINR) as $\gamma_1 \geq \gamma_2 \geq \gamma_3 \geq \cdots \geq \gamma_n \geq \gamma_{n+1} \geq \cdots \geq \gamma_N$. So user k can successfully decode the signal of user l if $\gamma_k > \gamma_l$. So the post-processing SINR for user

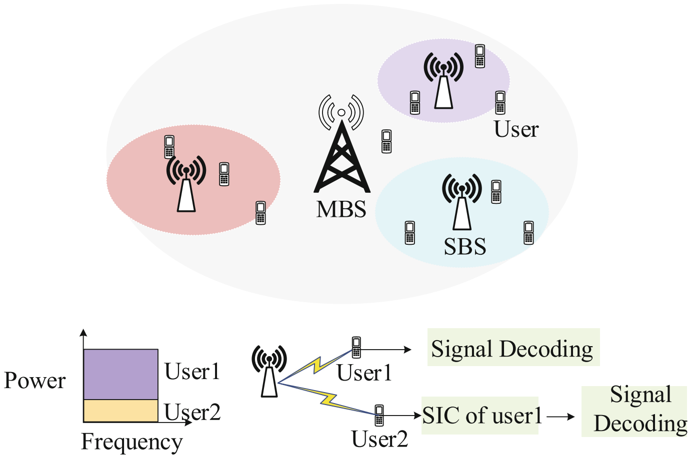

Fig. 1. System model of the studied network with NOMA

k with SBS j in RB n is denoted as

$$\gamma_{kj}^{n} = \frac{p_{kj}^{n} g_{kj}^{n}}{\sum_{i=n+1}^{N} p_{ij}^{n} g_{kj}^{n} + 1} \tag{2}$$

Assuming the signal is successfully decoded at user receiver and no error propagation occurs, the data rate for user k with SBS j in RB n can be written as

$$R_{kj}^{n} = B \log(1 + \gamma_{kj}^{n}) \tag{3}$$

2.2 Prediction Model with MMSE

Minimum Mean Square Error (MMSE) predictor is a simple and fast traffic prediction model in both theory and practice, which is suitable for the real time application and dynamic network environment [14]. The mathematical description of MMSE is shown as:

$$D_{t+1} = w_n D_t + \cdots + w_1 D_{t-n+1} + N_t \tag{4}$$

where n is the order of regression and N_t is white noise.

$\{D_t\}$ denotes a random linear process and D_{t+1} can be described with a linear combination of current and previous value of $\{D_t\}$. $\widehat{W}$ is a factor that describes the estimated weight vector, therefore the above equation can be changed to

$$\widehat{D}_{t+1} = \widehat{W} D' + N_t \tag{5}$$

where $\widehat{D}_{t+1}$ is the predicted value of D_{t+1}.

The expected value of squared errors is given by

$$E[e_t^2] = E[(D_{t+1} - \widehat{D}_{t+1})^2] \tag{6}$$

By minimizing the expected squared errors, the weight vector can be derived as

$$\widehat{W} = \Gamma G^{-1} \tag{7}$$

where G is the auto correlation matrix and Γ is an autocorrelation vector as given by

$$G = \begin{bmatrix} \rho_0 & \rho_1 & \cdots & \rho_{n-1} \\ \rho_1 & \rho_0 & \cdots & \rho_{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n-1} & \rho_{n-2} & \cdots & \rho_0 \end{bmatrix} \tag{8}$$

$$\Gamma = \begin{bmatrix} \rho_n \cdots \rho_1 \end{bmatrix} \tag{9}$$

Autocorrelations ρ_k can be obtained by

$$\rho_k = \frac{\sum_{t=1}^{n-k} (D_t - \overline{D})(D_{t+k} - \overline{D})}{\sum_{t=1}^{n} (D_t - \overline{D})^2} \tag{10}$$

3 Problem Formulation and Algorithm Design

3.1 Traffic Prediction

In this subsection, we introduce the traffic prediction procedure with MMSE as mentioned above. The data traffic of each SBS at each time t is recorded as the input of our MMSE traffic prediction model. Then the mean value of the input sequence is calculated and so as the autocorrelation of the sequence. According to the autocorrelation matrix, the next-time traffic can be estimated. The predicting traffic value of SBS_j is $\widehat{D}_{j,t+1}$ which is given by

$$\widehat{D}_{j,t+1} = \widehat{w}_j D_{j,t} + \cdots + \widehat{w}_1 D_{j,t-n+1} + N_t \tag{11}$$

The computing procedure is summarized in Algorithm 1.

3.2 Self-organized Resource Allocation Algorithm

To cope with the imbalance problem of resource allocation in NOMA system and low resource utility problem brought by fixed allocation, we propose a self-organized resource allocation algorithm in which the network resource is allocated automatically according to the traffic load predicted by the prediction

Algorithm 1. Traffic Prediction Based on MMSE

1: Initialization:
a)$D_{j,t}$ describes the current traffic of SBS_j and $D_{j,t-1}, D_{j,t-2}, \cdots, D_{j,t-n+1}$ denotes previous observation of traffic on SBS_j
b)$\{D_j\} = \{D_{j,t}, D_{j,t-1}, D_{j,t-2}, \cdots, D_{j,t-n+1}\}$ denotes the set of current and previous traffic
2: **for** $j = 1, 2, \cdots, J$ **do**
3: Calculate the mean value $\overline{D}$ of $\{D_j\}$
4: Calculate the autocorrelations ρ_k according to (10)
5: Obtain the matrix G and Γ based on the calculated ρ_k
6: Calculate $\widehat{W}$ according to (7)
7: Obtain the estimated traffic $\widehat{D}_{j,t+1}$ of time $t+1$ according to (5)
8: **end for**

model. The overall data rate is taken as the maximization goal which can be formulated as follows:

$$\begin{aligned} &\max \sum_{k,n,j} r_{kj}^n x_{kj}^n \\ s.t. \quad & x_{kj}^n \in \{0,1\}, k \in \mathcal{K}, j \in \mathcal{J}, n \in \mathcal{N} \\ & \sum_k p_{kj}^n < p_j^n, k \in \mathcal{K}, n \in \mathcal{N} \\ & \sum_{i,n} r_{ij}^n > D_{j,t+1}, i \in \mathcal{I}, j \in \mathcal{J}, n \in \mathcal{N} \\ & \sum_k \sum_n p_{kj}^n < p_{tot}, k \in \mathcal{K}, n \in \mathcal{N} \end{aligned} \tag{12}$$

where p_n represents the power allocated to n-th RB, p_{tot} represents the total transmission power.

Note that problem (12) is a non-linear integer programming problem which is a NP-hard problem that can not be solved in linear time scale, so we can derive a suboptimal solution for problem via QPSO algorithm.

QPSO has three major parts consist of particle position, fitness function and evolution equation. The solution to our problem is the particle position which contains two parts, the RB allocation and the power allocation for each SBS. Assuming that there are P particles, and the position of the p particle is expressed as:

$$Q_p = (Q_{p,1}, \cdots, Q_{p,j}, \cdots, Q_{p,J}) \tag{13}$$

where, $Q_{p,j}$ denotes the result of the resource allocation for SBS_j, it can be written as:

$$Q_{p,j} = (x_{11}^j, \cdots, x_{KN}^j, p_{11}^j, \cdots, p_{KN}^j) \ \ \forall j \in \mathcal{J} \tag{14}$$

where x_{kn}^j denotes that $user_k$ is connected with SBS_j on RB_n and p_{kn}^j is the corresponding transmission power.

The fitness function is derived from the formulated problem which is used to evaluate the performance of each particle. In this paper, the fitness function is the overall data rate of the system which is given as:

$$\mathbb{F}(x_{kn}^j, p_{kn}^j) = \sum_{k,n} r_{kn}^j x_{kn}^j \tag{15}$$

In QPSO, the evolution equation of particle p ($p = 1, \cdots, P$) is given as:

$$\begin{cases} \mathbf{Q}_p(m+1) = \mathbf{B}_p(m) + b|\mathbf{L}_{best}(m) - \mathbf{Q}_p(m)| \cdot ln(\frac{1}{u}) \\ \qquad\qquad\qquad\qquad\qquad\qquad \text{if } r \geq 0.5 \\ \mathbf{Q}_p(m+1) = \mathbf{B}_p(m) - b|\mathbf{L}_{best}(m) - \mathbf{Q}_p(m)| \cdot ln(\frac{1}{u}) \\ \qquad\qquad\qquad\qquad\qquad\qquad \text{if } r < 0.5 \end{cases} \tag{16}$$

where, m denotes the iteration time; b is the contraction-expansion coefficient, which can be used to control the algorithm convergence rate; u and r are both random variables between 0 and 1; and $\mathbf{L}_{best}(m)$ is the mean best position of all particles in the m iteration, which can be obtained by

$$\mathbf{L}_{best}(m) = \frac{1}{P} \sum_{p=1}^{P} \mathbf{B}_p^{pbest}(m) \tag{17}$$

where $\mathbf{B}_p^{pbest}(m)$ is the best position of the p-th particle in the m-th iteration. The $\mathbf{B}_p(m)$ in (16) is called local attractor of particle p in the m-th iteration, which can be given as:

$$\mathbf{B}_p(m) = \alpha \mathbf{B}_p^{pbest}(m) + (1 - \alpha)\mathbf{G}_{best}(m), \tag{18}$$

where α is a random variable varies from 0–1, and $\mathbf{G}_{best}(m)$ is the global best position of all particles in the m-th iteration. The detailed procedure of the proposed self-organized resource allocation algorithm based on traffic prediction (SORA-TP) is summarized in Algorithm 2.

3.3 Derivation of Evolved Balance Factor

Because the proposed algorithm illustrates a self-organized resource allocation method that automatically allocates the resource based on the result of traffic prediction, so more resource is allocated to the SBSs that have heavier traffic load as predicted. To evaluate this characteristic of the proposed algorithm, we take joint consideration of the overall data traffic distribution and the resource utility and derive the EBF as follows

$$\psi = \eta \lg \mathbb{F}(x_{kn}^j, p_{kn}^j) \tag{19}$$

where η denotes the spectrum utility which is given as follows:

$$\eta = \frac{\sum_{k,n} r_{kn} x_{kn}}{W} \tag{20}$$

With the proposed factor, the performance of the algorithm can be evaluated efficiently.

Algorithm 2. SORA-TP Algorithm

Initialization:
a)Set user number K, SBS number J, number of subcarriers N
b)The maximum number of iterations M, number of particles P
c)The position of each particle $\mathbf{P}_p(j)$, $j \in \mathcal{J}$, set of best position of each particle $\mathbf{B}_p^{pbest}(1) = \mathbf{Q}_p(1)$, and according to the fitness function choose a best position from $\mathbf{B}_p^{pbest}(1)$ as $\mathbf{G}_{best}$, $best_{fit} = \mathbb{F}(x(1), p(1))$
d)Set the initial traffic value sequence $\{D_{j,t}\}$ for each SBS_j at time t
for $j = 1, 2, \cdots, J$ **do**
  Calculate $D_{j,t+1}$ according to (5)-(10)
end for
for $m = 1, \cdots, M$ **do**
  for $p = 1, \cdots, P$ **do**
    Calculate $\mathbf{L}_{best}(m)$ and $\mathbf{B}_p(m)$ according to (17) and (18), respectively
    Calculate $\mathbf{L}_{best}(m) - \mathbf{Q}_p(m)$, set random variable b, u, r
    if $r < 0.5$ **then**
      $\mathbf{Q}_p(m+1) = \mathbf{B}_p(m) - b|\mathbf{L}_{best}(m) - \mathbf{Q}_p(m)| \cdot ln(\frac{1}{u})$
    else
      $\mathbf{Q}_p(m+1) = \mathbf{B}_p(m) + b|\mathbf{L}_{best}(m) - \mathbf{Q}_p(m)| \cdot ln(\frac{1}{u})$
    end if
    Calculate the fitness function $\mathbb{F}(x_{kn}^j, p_{kn}^j)$ according to (15)
    if $best_{fit} < \mathbb{F}(x_{kn}^j, p_{kn}^j)$ **then**
      Update the $best_{fit}$ value to $\mathbb{F}(x_{kn}^j, p_{kn}^j)$, and $\mathbf{G}_{best}(m) = \mathbf{B}_p^{pbest}(m)$
    else
      $best_{fit} = best_{fit}$, $\mathbf{G}_{best}(m) = \mathbf{G}_{best}(m)$
    end if
  end for
end for
Output the $\mathbf{G}_{best}$, and obtain the resource allocation scheme according to the $\mathbf{G}_{best}$

4 Simulation Results and Discussions

In this section, simulation results are presented to illustrate the performance of the proposed algorithm. We consider a two-layer HetNet with 9 SBSs covered by one MBS. And there are 5 to 25 users randomly distributed in this area. System bandwidth is 4.5 MHz and subcarrier bandwidth is 180 kHz, accordingly. Inter site distance of SBSs is 40 m. Thermal noise is -174 dBm/Hz and the maximum transmit power is limited to 1 W. To express the simulation results better, we also run the simulation of the resource allocation algorithm without traffic prediction (RA-NOMA) and resource allocation algorithm with orthogonal multiple access (RA-OMA) as contrast.

Figure 2 compares the throughput performance of the above three algorithms with the number of users. With the increase in the number of users, overall throughput of the three algorithms increases as well, for the reason that data rate is brought by users. The proposed algorithm has higher throughput compared to the other two resource allocation schemes. The reason is that in our proposed algorithm, the resource is allocated to SBSs according to the results of traffic

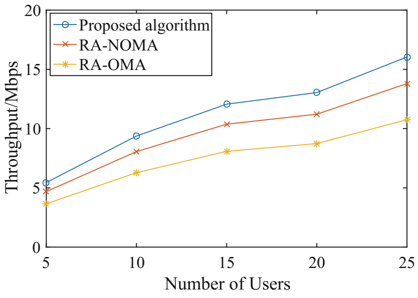

Fig. 2. Overall throughput versus the number of users

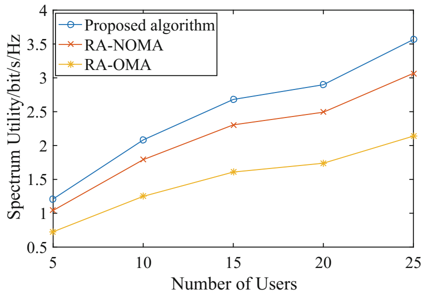

Fig. 3. Spectrum utility versus the number of users

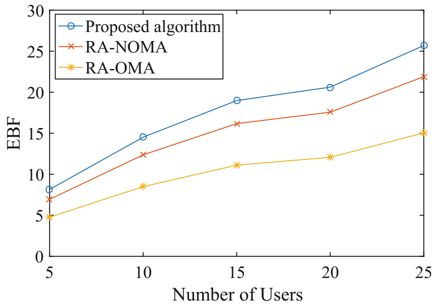

Fig. 4. EBF versus the number of users

prediction, so heavier the traffic load is, more resource will be allocated to the SBS. We can also see from the result that the throughput performance of RA-NOMA is better than RA-OMA. To explain, NOMA has higher resource utility than the orthogonal frequency division multiple access (OFDMA) and the SIC at the end of receiver can reduce the interference so SNR increased.

Figure 3 shows the curves of spectrum utility performance of different algorithms. The spectrum utility of the RA-OMA scheme is lowest because OFDMA system wastes some spectrum resources to avoid the interference. As the number of users increases, the spectrum utility becomes higher due to the increasing data rate brought by users. As for the proposed algorithm, the resources are allocated to where the traffic load is heavy, so the efficiency of resource utilization is higher than the comparison scheme.

Figure 4 describes the value of EBF with the number of users. The RA-OMA scheme has the worst EBF performance because neither the resource utility is efficient nor the throughput is high. It is noticeable that the EBF of the proposed algorithm is obviously higher than the other algorithm which denotes that the resource allocation in our proposed algorithm is adjusted automatically according to the distribution of data traffic load and achieves a better performance compared with other schemes.

5 Conclusion

In this paper, a resource allocation algorithm called SORA-TP in a two-tier HetNets with NOMA is proposed. To allocate the resource properly, a MMSE traffic prediction model is used which is appropriate for on-line traffic prediction. Then the resource allocation problem is formulated as a mixed integer non-linear programming (MINP) problem aiming at maximizing the overall throughput based on the prediction results. The optimization problem is difficult to solve in linear time scale so we propose an algorithm to obtain a suboptimal solution via QPSO algorithm. In order to illustrate the relationship between the predicted traffic and the allocated resource, a factor called EBF is derived which considers both resource utility and the overall throughput. The simulation results show that the proposed algorithm is efficient and outperforms the comparison schemes.

Acknowledgments. This paper is jointly sponsored by the National Natural Science Foundation of China (Grant No. 61671088) and the National Natural Science Foundation of China for the Youth (Grant No. 61501047).

References

1. Datta, S.N., Kalyanasundaram, S.: Optimal power allocation and user selection in non-orthogonal multiple access systems. In: 2016 IEEE Wireless Communications and Networking Conference, pp. 1–6, April 2016
2. Dai, L., Wang, B., Yuan, Y., Han, S., I, C., Wang, Z.: Non-orthogonal multiple access for 5G: solutions, challenges, opportunities, and future research trends. IEEE Commun. Mag. **53**(9), 74–81 (2015)
3. Wang, Y., Ren, B., Sun, S., Kang, S., Yue, X.: Analysis of non-orthogonal multiple access for 5G. China Commun. **13**(Supplement 2), 52–66 (2016)
4. Fang, F., Zhang, H., Cheng, J., Leung, V.C.M.: Energy-efficient resource allocation for downlink non-orthogonal multiple access network. IEEE Trans. Commun. **64**(9), 3722–3732 (2016)
5. Liu, F., Mahonen, P., Petrova, M.: Proportional fairness-based user pairing and power allocation for non-orthogonal multiple access. In: 2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), pp. 1127–1131, August 2015
6. Lei, L., Yuan, D., Ho, C.K., Sun, S.: Joint optimization of power and channel allocation with non-orthogonal multiple access for 5G cellular systems. In: 2015 IEEE Global Communications Conference (GLOBECOM), pp. 1–6, December 2015
7. Hagos, D.H., Kapitza, R.: Study on performance-centric offload strategies for LTE networks. In: 6th Joint IFIP Wireless and Mobile Networking Conference (WMNC), pp. 1–10, April 2013
8. Zhang, S., Gong, J., Zhou, S., Niu, Z.: How many small cells can be turned off via vertical offloading under a separation architecture? IEEE Trans. Wireless Commun. **14**(10), 5440–5453 (2015)
9. Jin, Z., Pan, Z., Liu, N., Li, W., Wu, J., Deng, T.: Dynamic pico switch on/off algorithm for energy saving in heterogeneous networks. In: 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), pp. 1–5, May 2015

10. Yao, C., Guo, J., Yang, C.: Achieving high throughput with predictive resource allocation. In: 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), pp. 768–772, December 2016
11. Yu, H., Cheung, M.H., Huang, L., Huang, J.: Power-delay tradeoff with predictive scheduling in integrated cellular and Wi-Fi networks. IEEE J. Sel. Areas Commun. **34**(4), 735–742 (2016)
12. Liu, Y., Li, X., Ji, H., Zhang, H.: A multiple APs cooperation access scheme for energy efficiency in UUDN with NOMA. In: 2017 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 1–5, May 2017
13. Sun, J., Fang, W., Wu, X., Palade, V., Xu, W.: Quantum-behaved particle swarm optimization: analysis of individual particle behavior and parameter selection. Evol. Comput. **20**(3), 349–393 (2012)
14. Li, J., Wang, X., Yu, R., Jia, J.: The adaptive routing algorithm depending on the traffic prediction model in cognitive networks. In: 2010 First International Conference on Pervasive Computing, Signal Processing and Applications, pp. 319–322, September 2010